Geostatistical Evaluation of Natural Tree Regeneration of a Disturbed Forest

José Germán Flores Garnica, David Arturo Moreno Gonzalez,
Juan de Dios Benavides Solorio Centro de Investigaciones del Pacífico Centro.
INIFAP. Parque Los Colomos S/N, Col. Providencia. Guadalajara, Jal.isco. México

Abstract—*The implementation of silvicultural strategies in a forest management has to guaranty forest sustainability, which is supported by an adequate regeneration. Therefore, quality and intensity of silvicultural practices is based on an accurate knowledge of the current spatial distribution of regeneration. At the same time, this regeneration is determined by the spatial distribution of many disturbing factors, such as fuel loadings, trees density, and grazing. However, regeneration mapping is not considered very often because its evaluation is both time and cost consuming. As a practical alternative, this study shows the results of a spatial evaluation of trees regeneration, where spatial distribution of regeneration is modeled. The data was obtained from 79 sample plots systematically distributed in a watershed of 1000 ha., at the saw of Tapalpa, Jalisco (México). Two interpolation alternatives were tested and compared: a) Inverse Distance Weighting [IDW]; and b) Ordinary Kriging (simple stochastic interpolation). Individuals between 0.30 and 2.5 m of height represented tree natural regeneration. The results showed that geostatistics technique (OK) was better in 50 percent of the cases, and deterministic technique (IDW) was better for the rest 50 percent. This suggest that not single interpolation technique has to be used in all situations. The results would support silvicultural strategies. It is suggested in further studies to use ancillary data, such as tree density, fuels, slope, and species distribution.*

Introduction

Forest sustainability is based in adequate forest management strategies. The implementation of silvicultural practices in a forest management has to guaranty forest sustainability, which is supported by an adequate tree regeneration (Moreno and others 1993). Therefore, quality and intensity of silviculture is based on an accurate knowledge of the current spatial distribution of regeneration. At the same time, this regeneration is determined by the spatial distribution of many disturbing factors, such as fuel loadings (Flores y Benavides, 1993), trees density, and grazing. As a consequence, forest sustainability is affected, costs are increased, and new management program must be developed (or at least adjusted). Therefore, before to implement a silvicultural program, we must develop methodologies that allows to know the spatial distribution. In this way, we will be capable to define which areas have a higher priority (for example, with low regeneration density), and establish a spatially better silvicultural planification. However, regeneration mapping is not considered very often because its evaluation is both time and cost consuming. Therefore, as a practical alternative, this study shows the results of a spatial evaluation of trees regeneration, where spatial distribution of regeneration is modeled. This modeling is based on the evaluating and comparing two interpolation techniques: inverse distance weighted and ordinary kiging. These techniques has been used successfully in other fields, such as mining, meteorology, and soil science (Laslett and others 1987; Webster y Oliver, 1989). However, their use has been limited in forestry (Hunner, 2000).

Methods

Study Area

The study area was a watershed located at 5 km to the west of Tapalpa town (Jalisco state), in the west-central region of Mexico (fig. 1), and it is located within the 19º 56' and 19º 58' North latitude; 103º 47' and 103º 51 West longitude (Benavides, 1987). This watershed has the following general characteristics: Altitude: 2060-2420 m.a.s.l. Mean annual rainfall: 901 mm. Mean temperature: 16.6ºC (Minimum mean annual 9.1ºC, Maximum mean annual 24.3ºC). This region corresponds to a temperate sub-humid climate (Benavides, 1987),

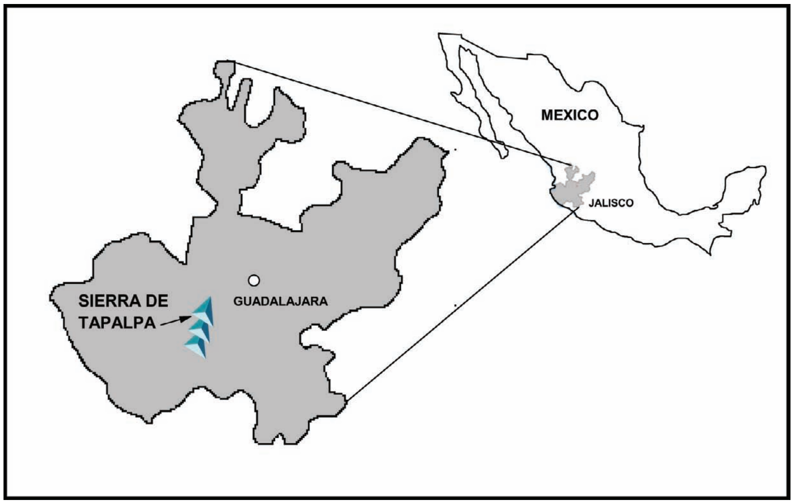

Figure 1. Approximate location of the Tapalpa Saw (Jalisco state, México), where the "El Carrizal" watershed is located.

and is dominated by *Pinus devoniana, Pinus oocarpa, Quercus rugosa; Quercus resinosa* and *Alnus*. The study area is mostly on north-facing slopes, at an altitude of 2110 m.a.s.l. In average, the slope varied between 5 and 65 percent.

Data Collection

The information used in this study was collected based on a specific forest inventory. Since we did not know well the study area, we used a systematic sample design. Sample plots were located every 500 m, within an area of around 1400 ha. Saplings were evaluated in a total of 79 100-m^2 circular sample plots, during a period of 30 days (between May and June, 2003). Plot center locations were determined using a global positioning system (GPS) receiver.

Data Analysis

The analysis of information was divided into two phases: I) Defining of fuel thematic maps: and II) Location of areas according to their potential fire effect. For the former, two spatial interpolation analyses were tested to get five thematic maps: (a) 1-HR fuels; (b) 10-HR fuels; (c) Downed woody; (d) Fine fuels weight; and (e) Fine fuels depth. The used techniques were:

Inverse distance weighting (power 2). This technique assumes that the value of an un-sampled point is a distance-weighted average of the values of observed points occurring nearby (Burrough and McDonnell, 1998). This interpolation technique gives more weight to closer observations than those that are farther away (Hunner, 2000). Such weights are inversely proportional to the distance between the point to be predicted and the data of nearby points computed, and are computed from a linear function (Burrough and McDonnell, 1998; Isaak and Srivastava, 1989):

$$\hat{\beta}*(x_0)=\frac{\sum_{i=1}^{n}\frac{1}{d_i^p}*\beta(x_i)}{\sum_{i=1}^{n}\frac{1}{d_i^p}}$$

where: $\hat{\beta}$ *(x0) = estimated value at un-sampled location x0; $\hat{\beta}$ (xi) = observed value at location xi; di = are the distances from each observed locations to the un-sampled point; p = distance exponent; n = number of sampled points.

Ordinary kriging, OK, is considered as the "best linear unbiased estimator" (Hunner, 2000; Isaaks and Srivastava, 1989): (a) Linear, because its estimates are weighted linear combinations of the available data; (b) Unbiased, because it tends to generate a mean square error equal to zero (E[Estimated(x0)-True(x0)] = 0, and Eλi = 0); and (c) Best, because it aims at minimizing the variance of the errors (E{[Estimated(x0) – True(x0)]2 = minimum). The following formulas are used to calculate the OK estimates (Hunner, 2000; Isaaks and Srivastava, 1989):

$$\hat{\rho}_{OK}(x_0)=\sum_{i=1}^{n}\lambda_i\cdot\rho(x_i)$$

where: $\hat{\rho}_{OK}(x_0)=$ ordinary kriging estimate at location x0; λi= the weight for sample point i at location xi; ρ (xi)= the value of the observed variable ρ at location xi. All the geostatistical estimations were defined under the assumption of an isotropic behavior of the data (omnidirectional approach).

Validation

To evaluate and select the interpolation techniques, cross-validation was applied(Goovaerts, 1997). This technique supported the calculation of prediction errors (differences between estimated and observed values [Hunner, 2000]), which were used to define the corresponding mean square error (MSE). The lower MSE was the criterion to select the best interpolation techniques (Flores, 2001). Mean square error (MSE) is a summary statistics that incorporates both the bias and the spread of the error distribution (MSE= variance + bias2), which is calculated as (Isaaks and Srivastava, 1989):

$$MSE=\frac{1}{n}\sum_{i=1}^{n}r^2$$

where: n= the number of sample points; and r= the residuals

Cross-validation was also applied to find the optimal number of nearest neighbors to include in the kriging processes.

Results and Discussion

Based on tree density and tree distribution, it was expected a high regeneration (individuals lower than 30 cm and saplings [up to 2.5 m]) density. However, there was very little regeneration lower than 30 cm, mostly at the north of the watershed. This distribution agrees with the distribution of higher dimensions (both diameter and height). In this portion we found also the higher densities of pine trees. Due to the low number of individuals lower tan 30 cm, we work with individuals between 0.65 and 2.5. m of height. I this way we define the following classes: (a) Saplings of main dominant species with < 60 cm of height (B-1A); (b) Saplings of main dominant species with 0.6–2.5 m of height (B-1B); (c) All the saplings of main dominant species (B1); (d) All the saplings of main co-dominant species (B2); (e) All the saplings of secondary co-dominant species (B3); and (f) All the saplings individuals (BT). The tree species of saplings were: *Pinus devoniana, P. oocarpa, P. leiophylla, P. lumholtzii, P. douglasiana, Quercus rugosa; Quercus resinosa y Alnus arbuta*. There were no dead saplings.

Following the kriging processes, the corresponding variograms for each class were defined. The resulting graphic is shown in figure 2, where in general a low spatial autocorrelation is observed: This condition is remarked in class B3, where the population variance is constant regardless the lag distance between sample plots. The models that better fit experimental variograms (semivariances distribution) corresponded to classes B-1A y B-1B, which showed a "Nugget effect" (Isaaks y Srivastava, 1989) relatively lower. In general, the maximum lag distance, where it is possible to appreciate a spatial autocorrelation, was 1,300 m. Most variograms fitted to spherical models, while classes B2 and B3 fitted better to an exponential and a lineal models.

In general, we can say that there was not a considerable difference of MSE values when comparing OK and IDW. However, it was OK was better in 50 percent of the classes, in IDW was the better option (table 1). These

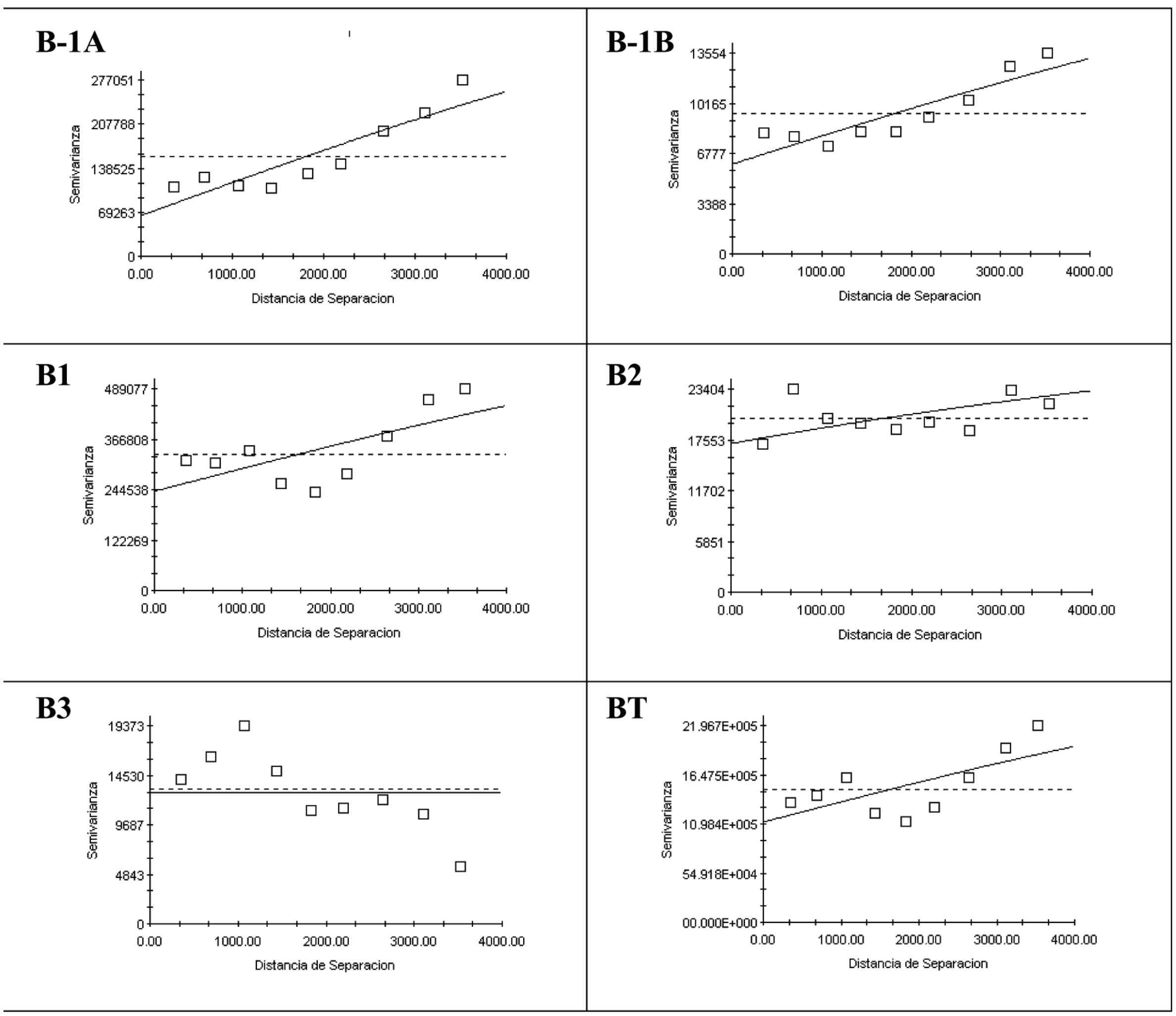

Figure 2. Variograms of spatial autocorrelation of saplings classes. Straight line shows the fitted model, the dot line shows the level of population variance.

Table 1. Mean square error resulted from the process of cross-validation of inverse distance weighted (IDW) and ordinary kriging interpolation techniques.

Sapling class	Idw	Kriging
B1A	135,005.81	125,967.41
B1B	8,858.21	8,869.73
B1	306,262.63	303,842.08
B2	20,676.40	21,259.80
B3	13,667.00	14,100.57
BT	729,924.72	715,040.54

results suggest that not always geostatistics alternatives are better. Nevertheless, variograms definition is a good tool to explore when could be possible to use OK (or other geostatistics technique). For example, in the three cases where OK was better the corresponding variograms defining better the spatial autocorrelation of sapling classes. The nugget effect was a lower, and the slope of the fitted model is higher than in the cases where IDW was better. This differences are more evident in the variogram of class B-1A, which resulted also in the higher MSE difference between OK and IDW (table 1). On the other hand, class B2 generated a variogram with a high nugget effect, and a very low slope. This defined a poor spatial autocorrelation of such class, which resulted in a better performance of IDW. There are two possible reason of such differences: i) a low number of sample plot with saplings in the corresponding class; and ii) geostatistics techniques are highly influenced in both the spatial autocorrelation the variable of interest, and the clustering of sample plots (Hunner, 2000). However, since the sample design was systematic, the latter condition could have a very low influence in the kriging process.

Figure 3 shows the continuous surface for each of the sapling classes generated from the best interpolation class. It is clear the graphical differences between

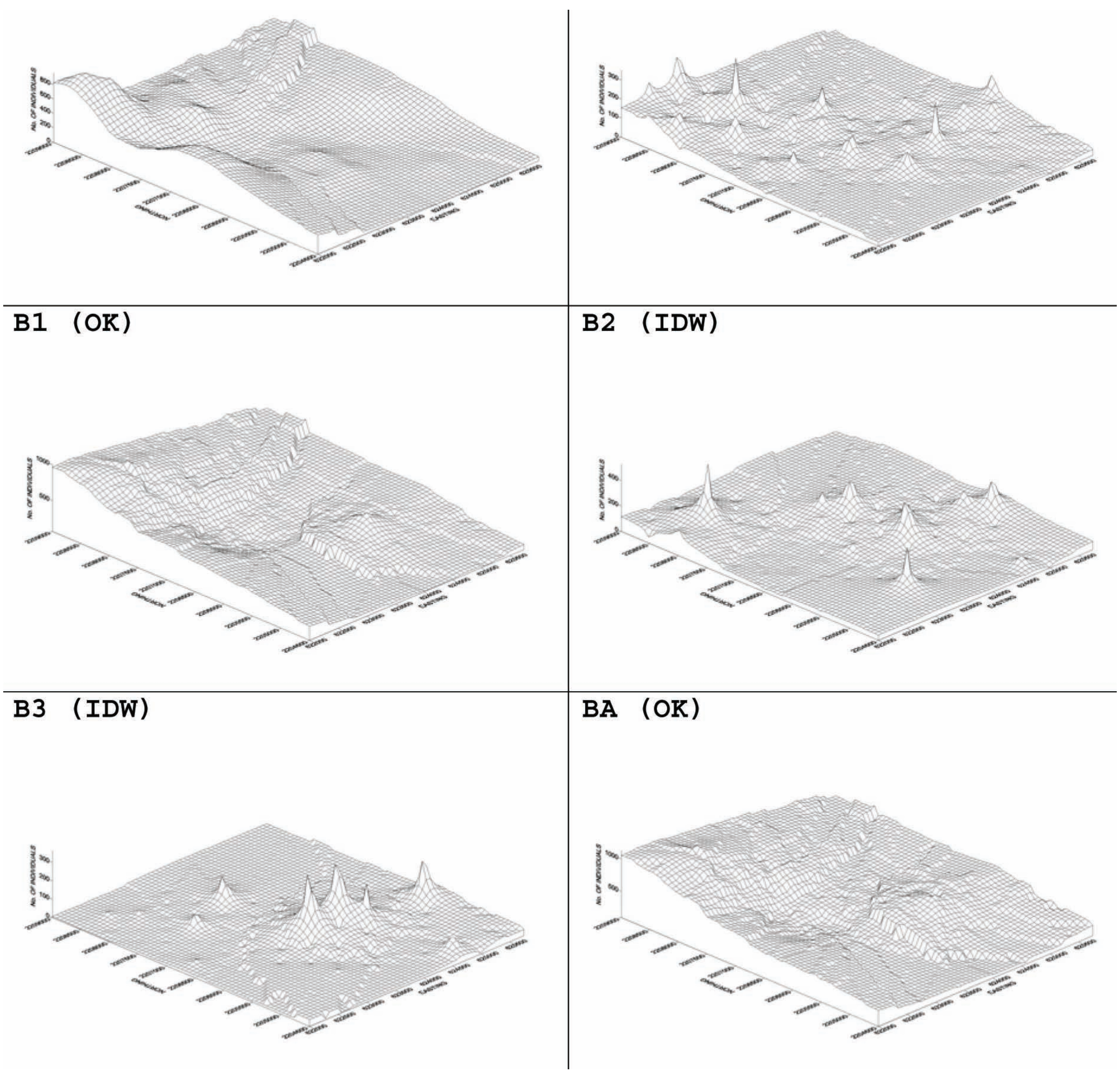

Figure 3. Continuous surfaces, generated by ordinary kriging (OK) and inverse distance weighted (IDW), representing the spatial variation of sapling classes.

continuous surfaces generated by OK and those generated by IDW. As it was mentioned, this difference could be the result of a low number of sample plots with saplings (mainly in the cases of classes B-1B, B2, and B3). This condition is better represented with the continuous surfaces generated by IDW, where it is easy it appreciate the locations of sample plots with a considerable higher number of saplings (relatively with the surrounded plots). When the number of sample plots with sapling was higher, such in the case of B-1A, B1, and BA, OK generate a smoother surface.

In general, natural regeneration is higher at the north of the watershed, which is logic if we consider that in that portion we found the better tree populations (specifically pine species). This spatial behavior was well defined for those dominant species (B-1A class). On the other hand, the spatial behavior of co-dominant species was better represented with the continuous surfaces generated by IDW. Considering all the sampled saplings (class BA) the resulting continuous surfaces is smoother. Which represent a decrease of sapling number going from north to south of the watershed.

Conclusions

To look for the best, or at least the more ad equated, spatial interpolation technique is a iterative process. In this study none of the used techniques generated the best results in all the cases, which agree with the results of other studies (Asli y Marcotte, 1995; Phillips and others 1997). However, it was important to consider the spatial autocorrelation of the studied classes, because it let us to define when OK could be better than IDW. The graphical representation of such autocorrelation, through the corresponding variograms, was a important factor in order to define strong autocorrelation. When OK was used, a spherical model fitted better to the corresponding experimental variograms (generating the lower MSE values). This implies a clear influence the "nugget" effect, with a gradual proximity to the corresponding "sill" and to the variogram range (Burrough y McDonnell, 1998).

The fact that IDW was better in 50 percent of the cases could be attributed to the following conditions: a) When data is abundant, most interpolation techniques produce similar results (Flores, 2001). In this study, because we have low spatial variability, it is considered that data were abundant (79 sample plots within 1400 ha). b) 2) Geostatistics techniques consider the data clustering. Since the used sampling design was systematic, this factor could have a low influence (Stein, 1999); and c) Geostatistic techniques assume that variable to interpolate show a normal distribution (Armostrong, 1998; Weber y Engud, 1994). Although this condition was true in most cases, it was not strong.

The continuous surface resulted in this study will support the generation of thematic maps of regeneration. These maps could be used to establish better spatial strategies to implement silvicultural activities. However, regeneration information has to be related to the spatial distribution of other factors, mainly slope, tree age, tree density, tree species composition. Nevertheless, regeneration maps will help to establish those areas with higher priority. Also we could define where we can establish multiple production systems, such as forestry and cattle, or forestry and eco-tourism. The main goal will be to take care of those areas where natural regeneration is located. On the other hand, based on the regeneration maps, we could define the location and the size of those areas that require artificial regeneration.

Finally, it is suggested to test other interpolation alternatives, mainly those that consider ancillary data. We could have better results if we relate tree regeneration with other factor of the forest environment, such as tree density, tree age, tree diameter, slope, aspect, and altitude.

References

Armstrong, M. 1998. Basic linear geostatistics. Springer, New York. 153 pp.

Asli, M. and Marcotte, D. 1995. Comparison of approaches to spatial estimation in a Bivariate context. Mathematical Geology, 27(5): 641-658.

Benavides S., J.D. 1987. Estimación de la calidad de sitio mediante indices de sitio del Pinus michoacana cornuta Martínez y Pinus oocarpa Schiede, para el A.D. F. Tapalpa, Estado de Jalisco. Tesis de Licenciatura. División de Ciencias Forestales. U.A. Chapingo. Chapingo, México. 80 pp.

Burrough, P. A. and McDonnell, R. 1998. Principles of geographical information systems. Oxford University Press. 333 p.

Flores G., J.G. 2001. Modeling the spatial variability of forest fuel arrays. Ph.D. Dissertation. Dept. For.Sc. Colorado State University. 184 p.

Flores G., J.G. and Benavides S., J.D. 1993. Quemas controladas y su efecto en los nutrimentos del suelo en un rodal de pino. Amatl 24-25, 6(1-2). Boletin de Difusion del Instituto de Madera, Celulosa y Papel. U. de Guadalajara.

Goovaerts, P. 1997. Geostatistics for natural resources evaluation. Applied geostatistics series. Oxford University Press. 483 p.

Hunner, G. 2000. Modeling forest stand structure using geostatistics, geographic information systems, and remote sensing. Ph.D. Dissertation. Colorado State University. 217 p.

Isaaks, E. H. and Srivastava, R. M. 1989. An introduction to applied geostatistics. Oxford University Press. 561 p.

Laslett, G. M.; McBratney, A. B.; Pahl, P. J.; Hutchinson, M. F. 1987. Comparison of several spatial prediction methods for soil pH. Journal of Soil Science, 38:325-341.

Moreno, G., D.A.; Manzanilla, H.; Talavera Z., E. 1993. Método “tocón a tocón” para cortas de aclareo y regeneración. Folleto Técnico No. 2. Campo Forestal Colomos. CIRPAC. INIFAP. SARH. 16 p.

Phillips, D.L.; Lee, E.H.; Herstrom, A.A.; Hogsett, W.E.; Tingey, D.T. 1997. Use of auxiliary data for spatial interpolation of ozone exposure in southeastern forests. Environmetrics, 8: 43-61.

Stein, M.L. 1999. Interpolation of spatial data. Some theory for kriging. Springer. 247 p.

Weber, D.D. and Engud, E.J. 1994. Evaluation and comparison of spatial interpolators II. Mathematical Geology, 26: 589-604.

Webster, R. and Oliver, M.A. 1989. Optimal interpolation and isarithmic mapping of soil properties. VI Disjunctive kriging and mapping the conditional probability. Journal of Soil Science, 40: 497-512.